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Sample greedy gossip distributed Kalman filter

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ABSTRACT

This paper investigates the problem of distributed state estimation over a low-cost sensor network and proposes a new sample greedy gossip distributed Kalman filter. The proposed algorithm leverages the information weighted fusion concept and the sample greedy gossip averaging protocol. By introducing a stochastic sampling strategy in the greedy sensor node selection process, the proposed algorithm finds a suboptimal communication path for each local sensor node during the process of information exchange. Theoretical analysis on global convergence and uniform boundedness is also performed to investigate the characteristics of the proposed distributed Kalman filter. The main advantage of the proposed algorithm is that it provides well trade-off between communication burden and estimation performance. Extensive empirical numerical simulations are carried out to demonstrate the effectiveness of the proposed algorithm.

1. Introduction

Target tracking and state estimation over a wireless sensor network have attracted increasing attention thanks to their critical importance in a wide range of real-world applications [1–7]. Employment of multiple sensors to cooperatively perform large-sensing tasks have become a viable option along with dramatic technical advancements in low-cost, lightweight and power efficient sensors. The issue is that these sensors are generally subject to reduced accuracy and reliability. It is well known that a proper fusion strategy could overcome such an issue as it is able to improve the quality of local estimation beyond their individual limitations and current status [8,9]. Therefore, it is of paramount importance to develop proper fusion algorithms, which synergistically integrate the redundant information and effectively complement the limitations of each sensor node, for low-cost sensor networks.

An immediate option for the fusion architecture would be centralised one which requires a fusion centre, collecting and processing the data from all local sensors simultaneously. The benefit of the centralised fusion is the performance: centralised Kalman filter (CKF) is known to be Bayesian optimal in multi-sensor target tracking. The issue is that it is inherently vulnerable to the single point failure and is not scalable. Unlike centralised fusion architecture, each sensor node in the distributed estimation only communicates with its connected neighbours in a peer-to-peer fashion. This could provide enhanced scalability and inherent redundancy, which results in strong robustness to sensor fault [8,10]. This paper adapts the distributed fusion architecture as the baseline fusion structure.

With the development of network theory, the control-theoretic consensus algorithm [11–14] was found to be a popular and powerful tool in designing distributed Kalman filters (DKFs). The strength of consensus algorithms is that they are able to perform network-wide computing tasks in a distributed manner. By applying the average consensus algorithm in local estimated state fusion, Olfati-Saber [15] developed a Kalman consensus filter (KCF) for distributed estimation. A theoretical analysis on stability and performance bound was performed later in [16]. The limitation of KCF is the choice of averaging only on local estimated states and therefore this algorithm cannot guarantee asymptotic convergence to the optimal CKF and cannot handle the naive sensors, i.e., targets are outside the sensors' field-of-view [17]. The covariance matrices also contain valuable information that could be leveraged to improve the fusion performance. For this reason, the authors in [18–20] proposed to perform average consensus on local measurement vectors and innovation covariances to match with the CKF in a distributed way. Another way of utilising covariance matrices is so-called consensus on information, which was developed based on the concept of covariance intersection [21–23]. Inspired by the complementary features of consensus on measurement and consensus on information, the authors in [24–26] suggested an information weighted consensus filter (IWCF) to retain the advantages of both algorithms.

Distributed estimation has also been investigated from the perspective of gossip process or randomised consensus in recent years. The authors in [27,28] developed a gossip interactive Kalman filter (GIKF) by randomly selecting a neighbour for each sensor node to swap their

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prior estimates and the corresponding error covariances in measurement update. The main promising feature of GIKF is that it offers reduced communication burden, compared to average-consensus-based DKFs, as each local sensor node only communicates with one of its connected neighbours. Based on the similar concept as KCF, the authors in [29] developed a new variant of DKF by exploiting the randomised gossip process to fuse the local state estimates. At every round of gossip iteration, each sensor randomly selects a locally-connected neighbour node and performs averaging on these two nodes. By performing gossip on local measurements and innovation covariances, a different randomised gossip DKF (RG-DKF) was proposed in [30] to approximate the CKF. Although RG-DKF has lower computational burden at each gossip iteration, its convergence speed is relatively slow due to the randomised nature. Unlike [30], a deterministic communication strategy using greedy gossip was suggested in [31] to develop a DKF, thus termed greedy gossip DKF (GG-DKF), that can improve the convergence rate of the gossip process. However, GG-DKF requires each local sensor to communicate with all its neighbouring sensor nodes connected to find the optimal path. This procedure consequently increases the communication load and might not be suitable for the employment of low-cost sensors [1].

Motivated by the aforementioned observations, this paper develops a new variant of gossip-based DKF. The algorithm developed is a generalised version of gossip-based DKFs and exhibits positive features of both RG-DKF and GG-DKF. To achieve this, we propose to leverage the recently proposed sample greedy gossip process (SGG) [32], which enables the proposed algorithm to find a suboptimal communication path for each local sensor node. To this end, the proposed gossip-based DKF approach is termed as sample greedy gossip DKF (SGG-DKF). Instead of finding the optimal path of each node in a greedy manner, SGG-DKF performs greedy node selection strategy among a randomly selected active sensor node set. This allows the proposed algorithm to make the expected size of the active sensor node set smaller than the number of locally-connected neighbours. Selection of the sensor activation probability enables us to properly balance the communication cost and estimation performance. This implies that SGG-DKF can reduce the communication cost in the average sense while retaining the estimation accuracy.

This paper proposes to utilise the information weighted fusion in the proposed SGG-DKF. Note that previous gossip-based DKF approaches utilise the concepts of measurement vector fusion (MVF) [30,31]. It is shown that the DKF based on MVF guarantees convergence to the centralised solution with infinite number of iterations. With a limited number of iterations, which is the case in practice, DKF using MVF could yield inconsistent local estimates. This might result in the auto-correlation problem in local estimates. Therefore, greedy gossip based on the concepts of MVF might be subject to poor performance with small number of gossip iterations. This issue can be relaxed by using the information weighted fusion as it preserves the consistency in local estimates.

Theoretical analysis shows that the proposed SGG-DKF guarantees asymptotic convergence to the centralised Kalman filter (CKF). For realistic application with finite number of gossip iterations, we show that the fused covariance matrix is uniformly bounded. Performance of the proposed algorithm is investigated by extensive Monte Carlo comparisons with RG-DKF and GG-DKF. The results reveal that the proposed algorithm converges to the optimal CKF with comparable speed to the GG-DKF, but with significantly less communication overhead. The results also indicate that the proposed algorithm significantly outperforms previous MVF-based gossip DKFs [30,31] in terms of tracking accuracy.

The rest of the paper is organised as follows. Section 2 introduces of the Bayesian optimal centralised solution. Section 3 presents the details of the proposed SGG-DKF algorithm, followed by theoretical analysis provided in Section 4. Finally, some numerical simulations and conclusions are offered.

2. Centralised Kalman filter: A benchmark

An optimal fusion strategy and benchmark for performance evaluation of distributed state estimation algorithms is the CKF, which processes all sensors' measurements simultaneously through a fusion centre. For this reason, this section will briefly review the centralised solution to facilitate the analysis carried out in the following sections. To begin with, consider a linear stochastic discrete-time system with N sensors as:

$$\begin{aligned} x_{k+1} &= F_k x_k + \omega_k \\ z_{k,i} &= H_{k,i} x_k + \upsilon_{k,i}, \quad i = 1, 2, \dots, N \end{aligned} \tag{1}$$

where $x_k \in \mathbb{R}^n$ denotes the system state vector at time instant k; $z_{k,i} \in \mathbb{R}^{m_i}$ represents the measurement vector of the ith sensor at time instant k. Matrices F_k and $H_{k,i}$ stand for the system transition and measurement matrices, respectively. ω_k and $\upsilon_{k,i}$ are uncorrelated white noises with zero mean and variances Q_k and $R_{k,i}$. For simplicity, it is usually assumed that the measurement noise is uncorrelated across the sensor nodes.

Define $x_{k|k-1}$ as the prior estimate of x_k and $P_{k|k-1}$ as the corresponding error covariance. Then, the Bayesian optimal centralised estimation of state x_k can be obtained using the information filter as [33]

$$\begin{aligned} P_{k|k}^{-1} x_{k|k} &= P_{k|k-1}^{-1} x_{k|k-1} + \sum_{i=1}^{N} H_{k,i}^T R_{k,i}^{-1} z_{k,i} \\ P_{k|k}^{-1} &= P_{k|k-1}^{-1} + \sum_{i=1}^{N} H_{k,i}^T R_{k,i}^{-1} H_{k,i} \end{aligned} \tag{2}$$

It is clear that centralised estimation (2) requires a fusion centre to collect information from all sensors. The centralised solution will be utilised as a benchmark for the performance comparison and evaluation of the distributed KF developed in the following sections.

3. Algorithm development

This section develops a new DKF algorithm by leveraging sample greedy gossip and information weighted fusion. Before presenting the details of the proposed distributed estimation algorithm, we briefly review the basic concept the sample greedy gossip process proposed in [32] for the completeness of the paper.

3.1. Sample greedy gossip process

We consider a network of N sensors and model the network topology as an undirected graph $\mathcal{G} = (\mathcal{V}, \mathcal{E})$, where $\mathcal{V} = \{1, 2, \dots, N\}$ represents the sensor node set and $\mathcal{E} \subset \mathcal{V} \times \mathcal{V}$ denotes the edge set. If sensor nodes s and t can directly communicate with each other, then $(s, t) \in \mathcal{E}$. For notation convenience, we define $\mathcal{N}_s$ as the set of the sensor nodes connected to the sth sensor (not including s) and $|\mathcal{N}_s|$ as the cardinality of set $\mathcal{N}_s$. Denote $\mathcal{N}_s \triangleq \{Sn(1), Sn(2), \dots, Sn(|\mathcal{N}_s|)\}$ with $Sn(i) \in \{1, 2, \dots, N\}$ for all $i \in \{1, 2, \dots, |\mathcal{N}_s|\}$.

Define a_s as the available information from the sth sensor and is initialised as $a_s(0)$. The objective of gossip algorithms is to enforce all local sensors to make an agreement on the initial average $\frac{1}{N}\sum_{s=1}^{N} a_s(0)$ by sharing information through locally-connected neighbours. At the lth round of the randomised gossip iterations, a sensor node $s \in \mathcal{V}$ is randomly selected for information exchange and this sensor randomly picks a connected node $t \in \mathcal{N}_s$ to perform information average [34]

$$a_s(l) = a_t(l) = \frac{a_s(l-1) + a_t(l-1)}{2} \tag{3}$$

Unlike randomised gossip, the greedy gossip algorithm employs a deterministic procedure to select an optimal communication node t that provides the largest information discrepancy for sensor s, that is [35]

$$t^* = \max_{t \in \mathcal{N}_s} \left[a_s(l) - a_t(l)\right]^2 \tag{4}$$

After finding t^*, the two sensors perform information averaging using Eq. (3). Compared with the original randomised gossip process, the greedy gossip algorithm is proved to provide improved convergence speed. However, this strategy requires each local sensor to communicate with all its neighbouring sensor nodes connected to find the optimal path. This procedure consequently increases the communication overload and might not be suitable for the employment of low-cost sensors [1].

Motivated by the complementary properties of randomised gossip and greedy gossip, the authors in [32] proposed a new sample greedy gossip, which enjoys the advantages of both randomised gossip and greedy gossip: relatively faster convergence speed and lower communication burden. During each round of sample greedy gossip iteration, all sensors in $\mathcal{N}_s$ generate a sample, i.e., q_i for all $i \in \{1, 2, \dots, |\mathcal{N}_s|\}$, from uniform distribution $\mathcal{U}(0,1)$. Each sensor from $\mathcal{N}_s$ is then activated with probability $p \in [0,1]$: if $q_i \le p$, sensor $Sn(i)$ decides to actively communicate with node s, i.e., sensor $Sn(i)$ is included in $\mathcal{A}_s$. The sample greedy gossip then employs the greedy sensor selection strategy to a random active sensor node set $\mathcal{A}_s \subset \mathcal{N}_s$ to find a suboptimal node t in communication with the sth sensor, i.e.,

$$t^* = \max_{t\in\mathcal{A}_s} \left[a_s(l) - a_t(l)\right]^2 \tag{5}$$

and utilises Eq. (3) to update local information. If no sensor has been activated by the sampling strategy, i.e., $\mathcal{A}_s = \emptyset$, the randomised gossip process is utilised for information update. The pseudo code of the sample greedy gossip algorithm is summarised in Algorithm 1. The following lemma analyses the asymptotic convergence performance of the SGG algorithm.

Lemma 1. *For connected sensor network, i.e., any two nodes can communicate with each other through a multi-hop path, the sample greedy gossip ensures asymptotic convergence to the initial average, i.e, [32]*

$$\lim_{l\to\infty} a(l) = \frac{1}{N}\sum_{s=1}^{N} a_s(0) \tag{6}$$

Proof. For the completeness of the paper, we briefly present the proof of Lemma 1. Detailed analysis of the convergence speed can be found at [32]. Denote $a(l) = \left[a_1(l), a_2(l), \dots, a_N(l)\right]^T$ and define $\bar{a}$ as a column vector with each element being $\frac{1}{N}\sum_{l=1}^{N} a_l(0)$. Assume that agents s and t perform gossip at the lth iteration of SGG, then the recursive update of SGG can be obtained as

$$a(l) = a(l-1) - \frac{1}{2}g(l) \tag{7}$$

where $g(l) \in \mathbb{R}^N$ is a column vector with its elements being

$$g_i(l) = \begin{cases} a_s(l-1) - a_t(l-1), & \text{for } i = s \\ -\left(a_s(l-1) - a_t(l-1)\right), & \text{for } i = t \\ 0, & \text{otherwise} \end{cases} \tag{8}$$

Based on Eq. (7), the recursive update of the squared error is determined as

$$\begin{aligned} \|a(l) - \bar{a}\|^2 &= \left\|a(l-1) - \tfrac{1}{2}g(l) - \bar{a}\right\|^2 \\ &= \|a(l-1) - \bar{a}\|^2 - \left[a(l-1) - \bar{a}\right]^T g(l) + \tfrac{1}{4}\|g(l)\|^2 \\ &= \|a(l-1) - \bar{a}\|^2 - \tfrac{1}{2}\left[a_s(l-1) - a_t(l-1)\right]^2 \end{aligned} \tag{9}$$

Note that both s and t are random in the proposed SGG. For this reason, we will examine the expected squared error, i.e., $\mathbb{E}\left[\|a(l) - \bar{a}\|^2\right]$, in the following analysis. Taking the expectation on $\left[a_s(l-1) - a_t(l-1)\right]^2$ gives

$$\begin{aligned} &\mathbb{E}\left\{\left[a_s(l-1) - a_t(l-1)\right]^2\right\} \\ &= \frac{1}{N}\sum_{s=1}^{N}\sum_{m=1}^{|\mathcal{N}_s|} p^m(1-p)^{|\mathcal{N}_s|-m} \\ &\quad\times \sum_{\mathcal{N}_{s,m}\in\{\mathcal{N}_{s,m}\}} \max_{t\in\mathcal{N}_{s,m}} \left[a_s(l-1) - a_t(l-1)\right]^2 \\ &\quad+ \frac{1}{N}\sum_{s=1}^{N}(1-p)^{|\mathcal{N}_s|}\frac{1}{|\mathcal{N}_s|}\sum_{t\in\mathcal{N}_s}\left[a_s(l-1) - a_t(l-1)\right]^2 \end{aligned} \tag{10}$$

where $\mathcal{N}_{s,m}$ denotes a set of m nodes, randomly drawn from $\mathcal{N}_s$ and $\{\mathcal{N}_{s,m}\}$ stands for the set that includes all possible $\mathcal{N}_{s,m}$.

Note that the first term on the right hand side of Eq. (10) refers to the case where $1 \le m \le |\mathcal{N}_s|$ nodes decide to communicate with the sth node, and the second term implies the case where no node has been activated by the sampling procedure. As stated in Algorithm 1, if no node decides to communicate with node s during the sampling phase, we perform the randomised gossip for update. From Eq. (10), it is clear that $\mathbb{E}\left\{\left[a_s(l-1) - a_t(l-1)\right]^2\right\} \ge 0$, where the equality holds if and only if $a(l-1) = \bar{a}$. This means that, unless all nodes make agreement on the average state $\bar{a}$, the proposed SGG algorithm will make progress in expectation towards the average state $\bar{a}$. Moreover, by repeatedly applying recursion (9) and taking the expectation, we have

$$\begin{aligned} \mathbb{E}\left[\|a(l) - \bar{a}\|^2\right] &= \mathbb{E}\left[\|a(l-1) - \bar{a}\|^2\right] \\ &\quad - \tfrac{1}{2}\mathbb{E}\left\{\left[a_s(l-1) - a_t(l-1)\right]^2\right\} \\ &= \mathbb{E}\left[\|a(0) - \bar{a}\|^2\right] - \tfrac{1}{2}\textstyle\sum_{i=1}^{l}\mathbb{E}\left\{\left[a_s(i-1) - a_t(i-1)\right]^2\right\} \end{aligned} \tag{11}$$

Since $\mathbb{E}\left[\|a(l) - \bar{a}\|^2\right] \ge 0$, we have

$$\mathbb{E}\left[\|a(0) - \bar{a}\|^2\right] \ge \frac{1}{2}\sum_{i=1}^{l}\mathbb{E}\left\{\left[a_s(i-1) - a_t(i-1)\right]^2\right\} \tag{12}$$

which implies that $\mathbb{E}\left\{\left[a_s(l-1) - a_t(l-1)\right]^2\right\} \to 0$ as $l \to \infty$. As the solution $a(l) = \bar{a}$ is the only stationary point of stochastic recursion (10), the proposed SGG algorithm guarantees asymptotic convergence to the average state $\bar{a}$.

Remark 1. It has been theoretically proved in [32] that the sample greedy gossip can be considered as a generalised version of the gossip algorithm that can trade-off between randomised gossip and greedy gossip: the sample greedy gossip becomes greedy gossip with $p = 1$ and reduces to randomised gossip with $p = 0$. Theoretical analysis reveals that the convergence speed of sample greedy gossip increases with the increase of sensor activation probability [32]. This means that we can choose a relatively large sensor activation probability to achieve fast convergence rate if the sensor network provides enough communication resource; otherwise, a small value of p would be a wise option.

3.2. Distributed Kalman filter design

At time instant k, every local sensor node predict the target state estimate based on previous estimate and available mode information as

$$\begin{aligned} x_{k|k-1,i} &= F_k x_{k-1|k-1,i} \\ P_{k|k-1,i} &= F_{k-1}P_{k-1|k-1,i}F_{k-1}^T + Q_{k-1} \end{aligned} \tag{13}$$

where $x_{k|k-1,i}$ and $x_{k-1|k-1,i}$, respectively, represent the state prediction at time instant k and update at time instant $k-1$ with corresponding error covariances $P_{k|k-1,i}$ and $P_{k-1|k-1,i}$ from sensor i.

Algorithm 1 Sample greedy gossip

Input: Initial local information $a_s(0)$, maximum iteration step L, node selection probability p
Output: Fused information $a_s(L)$

```
Randomly selects a sensor node s from the sensor network
for l = 1 : L do
    A_s = ∅                                ▷ Initialise the active sensor node set A_s
    for i = 1 : |N_s| do
        Sensor Sn(i) generates a sample q_i ~ U(0, 1)
        if q_i ≤ p then
            Sensor Sn(i) decides to actively communicate with sensor s
            A_s = A_s ∪ Sn(i)              ▷ Update the active sensor node set A_s
        end if
    end for
    if A_s ≠ ∅ then
        t* = max_{t∈A_s} [a_s(l−1) − a_t(l−1)]^2     ▷ Greedy node selection from A_s
        a_s(l) = a_{t*}(l) = 1/2 [a_s(l−1) + a_{t*}(l−1)]
    else
        Randomly selects a sensor node t from N_s     ▷ Randomised gossip
        a_s(l) = a_t(l) = 1/2 [a_s(l−1) + a_t(l−1)]
    end if
end for
```

After obtaining the one-step prediction by local Kalman filter, we are now interested in updating the local prediction via fusing information from locally-connected neighbours. As the information weighted fusion rule or the so-called parallel fusion has advantages of preserving local estimate consistency and guaranteed global convergence to the centralised solution [25,26], this fusion rule is leveraged in this paper to fuse the local estimates. That is, the information to be shared between two local sensor nodes is defined as

$$\begin{aligned} u_{k,i} &= \frac{1}{N} P_{k|k-1,i}^{-1} x_{k|k-1,i} + H_{k,i}^T R_{k,i}^{-1} z_{k,i} \\ U_{k,i} &= \frac{1}{N} P_{k|k-1,i}^{-1} + H_{k,i}^T R_{k,i}^{-1} H_{k,i} \end{aligned} \tag{14}$$

Note that the key of implementing sample greedy gossip in sensor fusion is to define a proper criterion to evaluate the similarity between two local estimates. For this reason, a statistical distance to quantify the similarity between $(u_{k,i}, U_{k,i})$ and $(u_{k,j}, U_{k,j})$ will be defined first. Notice that the residual of $u_{k,i}$ is give by

$$\tilde{u}_{k,i} = \frac{1}{N} P_{k|k-1,i}^{-1} \left(x_{k|k-1,i} - x_k \right) + H_{k,i}^T R_{k,i}^{-1} \left(z_{k,i} - H_{k,i} x_k \right) \tag{15}$$

Assume that $x_{k|k-1,i}$ is unbiased, i.e., $\mathbb{E}\left[x_{k|k-1,i}\right] = x_k$. Then, it is straightforward to verify that the covariance of $\tilde{u}_{k,i}$ is determined as

$$\mathbb{E}\left[\tilde{u}_{k,i} \tilde{u}_{k,i}^T\right] = U_{k,i} \tag{16}$$

Based on Eq. (16), the statistical difference between $(\tilde{u}_{k,i}, U_{k,i})$ and $(\tilde{u}_{k,j}, U_{k,j})$ can then be quantified by the Mahalanobis distance

$$d_{i,j} = \left(\tilde{u}_{k,i} - \tilde{u}_{k,j}\right)^T \left(U_{k,i} + U_{k,j}\right)^{-1} \left(\tilde{u}_{k,i} - \tilde{u}_{k,j}\right) \tag{17}$$

The issue of utilising the Mahalanobis distance $d_{i,j}$ as the similarity measure is that the information on true target state x_k is not available in practice. To address this problem, we assume that the previous time instant achieves fully average consensus, i.e., $x_{k-1|k-1,i} = x_{k-1|k-1,j}$ and $P_{k-1|k-1,i} = P_{k-1|k-1,j}$, $\forall i \neq j$. Note that this is a typical assumption in developing DKFs for sensor networks [1,25]. With this in mind, Eq. (17) reduces to

$$d_{i,j} = \left(u_{k,i} - u_{k,j}\right)^T \left(U_{k,i} + U_{k,j}\right)^{-1} \left(u_{k,i} - u_{k,j}\right) \tag{18}$$

By exploiting the Mahalanobis distance $d_{i,j}$ as a similarity measure between two local estimates, we can then implement the sample greedy gossip algorithm to find a suboptimal communication path for every local sensor node to fuse $(u_{k,i}, U_{k,i})$. After L iterations of the gossip process, the measurement update of the proposed DKF is then given by

$$\begin{aligned} x_{k|k,i} &= \left[U_{k,i}(L)\right]^{-1} u_{k,i}(L) \\ P_{k|k,i}^{-1} &= N U_{k,i}(L) \end{aligned} \tag{19}$$

The complete pseudo code of the proposed SGG-DKF is summarised in Algorithm 2.

Remark 2. In a practical scenario, not all sensors can get the measurement information of the target due to limited sensor field-of-view and non-unity detection probability. In the case where no measurement information of the target is available at the ith sensor, the quality of local estimation $x_{k|k}, i$ will be very poor and is far from the real state. Fusing this poor information with other relatively good local estimation could deteriorate the performance of the fused results . To accommodate this issue, we do not activate the sensors that cannot detect the target during the fusion process and hence do not perform the information fusion step. This simple strategy is helpful in improving the stability of the fusion process.

Remark 3. Compared to previously-developed gossip-based DKF algorithms [30,31], the following two improvements are made in the proposed approach: (1) the sample greedy gossip algorithm is utilised to exploit the benefits of both randomised gossip and greedy gossip; and (2) the information weighted fusion rule is leveraged in the proposed algorithm while [30,31] utilised the concept of MVF. Note that utilisation of the information weighted fusion enables the SGG-DKF algorithm to guarantee consistency in local estimates and thus could enhance the performance, especially in case of a small number of gossip iterations.

Remark 4. Note that the proposed SGG-DKF is developed based on assumption that the previous local estimates are converged. In real applications, however, only finite number of gossip iterations are acceptable, which means that $x_{k-1|k-1,i} \neq x_{k-1|k-1,j}$ and $P_{k-1|k-1,i} \neq P_{k-1|k-1,j}$. Therefore, all local estimates are auto-correlated during the fusion phase and thus SGG-DKF also suffers from the well-known auto-correlation problem. However, as the information weighted consensus concept incorporates covariance intersection, which is proved to be highly robust against the auto-correlation among local estimates. This issue, therefore, can also be alleviated by the proposed SGG-DKF.

4. Algorithm analysis

This section provides theoretical analysis on the convergence and boundedness of the proposed SGG-DKF algorithm. The main results are presented in Theorems 1 and 2.

Theorem 1. *For connected sensor network, the proposed SGG-DKF algorithm ensures asymptotic convergence to the optimal CKF.*

Proof. Define $y_{k,i} = P_{k|k-1,i}^{-1} x_{k|k-1,i}$, $Y_{k,i} = P_{k|k-1,i}^{-1}$, $q_{k,i} = H_{k,i}^T R_{k,i}^{-1} z_{k,i}$ and $\Omega_{k,i} = H_{k,i}^T R_{k,i}^{-1} H_{k,i}$. Then, Eq. (14) can be rewritten as

$$\begin{aligned} u_{k,i} &= \frac{1}{N} y_{k|k-1,i} + q_{k,i} \\ U_{k,i} &= \frac{1}{N} Y_{k|k-1,i} + \Omega_{k,i} \end{aligned} \tag{20}$$

According to Lemma 1, it is straightforward to verify that

$$\begin{aligned} \lim_{L\to\infty} u_{k,i}(L) &= \frac{1}{N} \sum_{i=1}^{N} \frac{y_{k,i}(0)}{N} + \frac{1}{N} \sum_{i=1}^{N} q_{k,i}(0) \\ \lim_{L\to\infty} U_{k,i}(L) &= \frac{1}{N} \sum_{i=1}^{N} \frac{Y_{k,i}(0)}{N} + \frac{1}{N} \sum_{i=1}^{N} \Omega_{k,i}(0) \end{aligned} \tag{21}$$

Algorithm 2 Sample greedy gossip distributed Kalman filter

Input: Previous target estimation $\{x_{k-1|k-1,i}, P_{k-1|k-1,i}\}$, received measurements $z_{k,i}$
Output: Current estimation $\{x_{k|k,i}, P_{k|k,i}\}$
(1) Prediction:

$$x_{k|k-1,i} = F_k x_{k-1|k-1,i}$$
$$P_{k|k-1,i} = F_{k-1} P_{k-1|k-1,i} F_{k-1}^T + Q_{k-1}$$

(2) Compute the information terms:

$$u_{k,i} = \frac{1}{N} P_{k|k-1,i}^{-1} x_{k|k-1,i} + H_{k,i}^T R_{k,i}^{-1} z_{k,i}$$
$$U_{k,i} = \frac{1}{N} P_{k|k-1,i}^{-1} + H_{k,i}^T R_{k,i}^{-1} H_{k,i}$$

(3) **for** $l = 0, 1, \dots, L$ **do**

Compute the Mahalanobis distance $d_{i,j}$

Use Algorithm 1 to find a local neighbour j^* which has the largest value of $d_{i,j^*}(l)$ among the active sensor nodes as

$$j^* = \begin{cases} \max_{j \in \mathcal{A}_i} d_{i,j}(l), & \mathcal{A}_i \neq \emptyset \\ \text{randomly picking from } \mathcal{N}_i, & \mathcal{A}_i = \emptyset \end{cases}$$

After finding j^*, perform information averaging

$$u_{k,i}(l) = \frac{1}{2}\left[u_{k,i}(l-1) + u_{k,j^*}(l-1)\right]$$
$$U_{k,i}(l) = \frac{1}{2}\left[U_{k,i}(l-1) + U_{k,j^*}(l-1)\right]$$

(4) Measurement update:

$$x_{k|k,i} = \left[U_{k,i}(L)\right]^{-1} u_{k,i}(L)$$
$$P_{k|k,i}^{-1} = N U_{k,i}(L)$$

As gossip on priors guarantees that all local sensors have the same priori estimates, i.e., $y_{k,i} = \frac{1}{N}\sum_{i=1}^N y_{k,i}(0)$ and $Y_{k,i} = \frac{1}{N}\sum_{i=1}^N Y_{k,i}(0)$, it is immediate to see that the proposed SGG-DKF with infinite number of iterations can recover the performance of centralised estimation by substituting Eq. (21) into the measurement update step in Algorithm 2.

Although the proposed SGG-DKF algorithm is shown to be asymptotically optimal, only limited number of gossip iterations is available in real applications. For this reason, Theorem 2 analyses the boundedness of the proposed algorithm with finite number of gossip iterations. Before giving the main results, the following two general assumptions are made.

Assumption 1. The system matrix F_k is invertible.

Assumption 2. The sensor network is collectively observable, i.e., the pair (F_k, H_k) is observable, where $H_k = \left[H_{k,1}^T, H_{k,2}^T, \dots, H_{k,N}^T\right]^T$.

Note that all sensor nodes are subject to the limited sensing capability. This means that it might be unreasonable to assume the local observability, i.e., the pair $(F_k, H_{k,i})$ is observable. This paper utilises the collective observability to define the observability of the sensor network. It is clear that the network is collectively observable if and only if the network is strongly connected, i.e., any two sensors are direct (one-hop) or indirect connected (multi-hop). The result of the boundedness of the fused covariance matrices is now presented in the following theorem.

Theorem 2. *Suppose that the sensor network is connected and that $P_{k-1|k-1,i}$ is positive-definite and under Assumptions 1 and 2, there exists an time instant b and a positive scalar α such that the fused covariance is uniformly bounded in the average sense as*

$$\mathbb{E}\left[P_{k+b|k+b,i}\right] \leq \alpha I_n \tag{22}$$

Here, the expectation is over all possible network connections.

Proof. According to the propagation of the prediction step in Kalman filter, we have

$$\begin{aligned} P_{k|k-1,i}^{-1} &= \left(F_{k-1} P_{k-1|k-1,i} F_{k-1}^T + Q_{k-1}\right)^{-1} \\ &= \left(F_{k-1}^{-1}\right)^T \left[P_{k-1|k-1,i} + F_{k-1}^{-1} Q_{k-1} \left(F_{k-1}^{-1}\right)^T\right]^{-1} F_{k-1}^{-1} \end{aligned} \tag{23}$$

Since the covariance of the process noise is bounded, there exists a positive scalar $\beta > 0$ such that

$$F_{k-1}^{-1} Q_{k-1} \left(F_{k-1}^{-1}\right)^T \leq \beta P_{k-1|k-1,i} \tag{24}$$

By choosing $\gamma = (1+\beta)^{-1}$, Eq. (23) can be reformulated as

$$P_{k|k-1,i}^{-1} \geq \gamma \left(F_{k-1}^{-1}\right)^T P_{k-1|k-1,i}^{-1} F_{k-1}^{-1} \tag{25}$$

After performing L steps of gossip iterations, we have

$$P_{k|k,i}^{-1} = \sum_{j=1}^N w_{i,j}^L P_{k|k-1,j}^{-1} + N \sum_{j=1}^N w_{i,j}^L H_{k,j}^T R_{k,j}^{-1} H_{k,j} \tag{26}$$

where $w_{i,j}^L$ denotes the (i,j)th element of the L-steps update matrix of the sample greedy gossip process.

Substituting Eq. (25) into Eq. (26) gives

$$\begin{aligned} P_{k|k,i}^{-1} \geq& \gamma \sum_{j=1}^N w_{i,j}^L \left(F_{k-1}^{-1}\right)^T P_{k-1|k-1,j}^{-1} F_{k-1}^{-1} \\ &+ N \sum_{j=1}^N w_{i,j}^L H_{k,j}^T R_{k,j}^{-1} H_{k,j} \end{aligned} \tag{27}$$

Applying the preceding inequality to $P_{k+b|k+b,i}^{-1}$ for b steps repeatedly yields

$$\begin{aligned} P_{k+b|k+b,i}^{-1} &\geq \gamma^b \sum_{j=1}^N w_{i,j}^{bL} \left(F_{k-1}^{-b}\right)^T P_{k-1|k-1,j}^{-1} F_{k-1}^{-b} \\ &+ N \sum_{j=1}^N \sum_{m=1}^b \gamma^{b-m} w_{i,j}^{(b-m+1)L} \left(F_{k-1}^{m-b}\right)^T H_{k,j}^T R_{k,j}^{-1} H_{k,j} F_{k-1}^{m-b} \\ &\geq N \sum_{j=1}^N \sum_{m=1}^b \gamma^{b-m} w_{i,j}^{(b-m+1)L} \left(F_{k-1}^{m-b}\right)^T H_{k,j}^T R_{k,j}^{-1} H_{k,j} F_{k-1}^{m-b} \end{aligned} \tag{28}$$

Denote the diameter of the undirected graph $\mathcal{G}$ as $\mathcal{D}(\mathcal{G})$. Then, there exists a path no longer than $\mathcal{D}(\mathcal{G})$ in which any two nodes are connected. Also note that the sample greedy gossip ensures the possibility that each local sensor node can communicate with all its connected neighbours. This means that if the number of gossip iterations satisfies $L \geq \mathcal{D}(\mathcal{G})$, we have

$$\mathbb{E}\left[w_{i,j}^{(b-m+1)L}\right] > 0 \tag{29}$$

Therefore, it can be concluded that there exist positive constants $\pi_{i,j}$ such that

$$\mathbb{E}\left[w_{i,j}^{(b-m+1)L}\right] \geq \pi_{i,j} > 0 \tag{30}$$

Substituting Eq. (30) into Eq. (28) gives

$$\begin{aligned} &\mathbb{E}\left[P_{k+b|k+b,i}^{-1}\right] \\ &\geq \sum_{j=1}^N \sum_{m=1}^b \gamma^{b-m} \pi_{i,j} \left(F_{k-1}^{m-b}\right)^T H_{k,j}^T R_{k,j}^{-1} H_{k,j} F_{k-1}^{m-b} \\ &\geq \gamma^{b-1} \pi_{i,\min} \sum_{j=1}^N \sum_{m=1}^b \left(F_{k-1}^{m-b}\right)^T H_{k,j}^T R_{k,j}^{-1} H_{k,j} F_{k-1}^{m-b} \end{aligned} \tag{31}$$

where $\pi_{i,\min} = \min_j\{\pi_{i,j}\}$. Since the sensor network is collectively observable, there exists $b > 0$ such that the Grammian matrix satisfies $\sum_{m=1}^{b}\left(F_{k-1}^{m-b}\right)^T H_{k,j}^T H_{k,j} F_{k-1}^{m-b} > 0$ for all j. Additionally, noting that the covariance matrix of the measurement noise is always positive-definite and bounded, we have

$$\sum_{j=1}^{N}\sum_{m=1}^{b}\left(F_{k-1}^{m-b}\right)^T H_{k,j}^T R_{k,j}^{-1} H_{k,j} F_{k-1}^{m-b} \geq \sigma I_n > 0 \tag{32}$$

where $\sigma > 0$. This subsequently indicates that there exists a positive scalar α such that the fused covariance is uniformly bounded in the average sense as $\mathbb{E}\left[P_{k+b|k+b,i}\right] \leq \alpha I_n$ where $\alpha = (\gamma^{b-1}\pi_{i,\min}\sigma)^{-1}$.

5. Numerical simulations

This section presents a performance evaluation of the proposed SGG-DKF algorithm with comparison to other approaches using Monte Carlo simulations.

5.1. Simulation setup

The target in the considered scenario randomly moves in a 500 m × 500 m rectangular area. We carried out extensive performance evaluation and comparison based on four different types of network topologies. Considering the page limit and similar tendency in the results, this paper demonstrates the simulation results on the two representative types of network topologies: random geometric network with 30 sensors and deterministic grid network with 25 sensors. Note that these two types of topologies are widely utilised in analysing the performance of distributed network-wide computation algorithms [35]. For the random geometric network, each sensor is randomly placed inside the surveillance region. Two sensors are connected in the random geometric network if their relative distance is less than 300 m in the simulations. Examples of these two different sensor topologies are presented in Fig. 1.

Each target's state is represented by a 4-D vector, with 2-D position and 2-D velocity components. In estimation update, the system equation is assumed to be the well-known constant velocity model, i.e.,

$$F_k = \begin{bmatrix} 1 & 0 & T_s & 0 \\ 0 & 1 & 0 & T_s \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \tag{33}$$

with $T_s = 1s$ being the sampling time. The variance of process noise of the considered constant velocity model is determined as

$$Q_k = \begin{bmatrix} 10 & 0 & 0 & 0 \\ 0 & 10 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \tag{34}$$

Each sensor collects position measurements at regular time instants $t_k = kT_s$, $k \in \{1, 2, \ldots, 100\}$, as

$$H_{k,i} = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \end{bmatrix} \tag{35}$$

The measurement noise is subject to a Gaussian white noise as $v_{k,i} \sim \mathcal{N}\left(\cdot; 0, R_{k,i}\right)$ with $R_{k,i} = diag\left(\sigma_r^2, \sigma_r^2\right)$, $\sigma_r = 10$ m. For initialisation, the covariance matrix of the target at sensor node i is chosen as $P_{0|0,i} = diag\,(100, 100, 10, 10)$. The initial state estimates are generated from a Gaussian distribution around the true target state with the covariance $P_{0|0,i}$. The starting point of the target is also randomly generated inside the surveillance region at every Monte Carlo run.

5.2. Performance metric

Let $x_{k|k,i}^j$ denote the estimated state of the target at sensor node i at time instant k of the jth Monte Carlo run and x_k^j represent the true target state at time instant k of the jth Monte Carlo run. The mean error (ME) of position estimation at time instant k, averaged over M Monte Carlo runs and N sensors, is defined as

$$\begin{aligned} \mathrm{ME}_k^{\mathrm{pos}} &= \frac{1}{MN}\sum_{i=1}^{N}\sum_{j=1}^{M}\left\|p_{k|k,i}^j - p_k^j\right\| \\ \mathrm{RMSE}_k^{\mathrm{pos}} &= \left(\frac{1}{MN}\sum_{i=1}^{N}\sum_{j=1}^{M}\left\|p_{k|k,i}^j - p_k^j\right\|^2\right)^{\frac{1}{2}} \end{aligned} \tag{36}$$

where $p_k^j = x_k^j(1:2)$ and $p_{k|k,i}^j = x_{k|k,i}^j(1:2)$ are true and estimated positions of the jth target.

For performance evaluation of the proposed algorithm, the time averaged ME and RMSE are utilised. These two metrics are computed as

$$\begin{aligned} \mathrm{ME}_{\mathrm{avg}}^{\mathrm{pos}} &= \frac{1}{T}\sum_{k=1}^{T}\mathrm{ME}_k^{\mathrm{pos}} \\ \mathrm{RMSE}_{\mathrm{avg}}^{\mathrm{pos}} &= \frac{1}{T}\sum_{k=1}^{T}\mathrm{RMSE}_k^{\mathrm{pos}} \end{aligned} \tag{37}$$

where $T = 100$ is the total number of time instants during the tracking period.

5.3. Comparison with different gossip algorithms

This subsection investigates performance of the proposed SGG-DKF algorithm, compared with RG-DKF and GG-DKF. The main objective of the performance comparison in this subsection is to validate the trade-off performance of the proposed SGG algorithm. For fair comparison, RG-DKF and GG-DKF algorithms are obtained by replacing the SGG process with RG and GG in SGG-DKF. Note that these two DKFs are also new algorithms that have never been proposed in the existing literatures. To better demonstrate the characteristics of different gossip algorithms, it is assumed that each sensor node has unlimited sensing range in this subsection.

In gossip-based distributed estimation, information transmission via multiple rounds of communication among locally-connected sensors are required and the performance highly depends on the number of iterations, i.e., L. In order to investigate the effect of the parameter L on the fusion performance, Monte Carlo comparisons of different gossip-based DKFs are carried out with respect to different number of iterations $L = 1, 2, \ldots, 10$. In the simulations, the sensor activation probability for implementing SGG is set as $p = 0.5$. The simulation results of ME of target position estimation and RMSE of target position estimation obtained from 500 Monte Carlo runs are depicted in Fig. 2. As shown in the figure, it can be noted that all tested DKFs asymptotically converge to the Bayesian optimal CKF. From Fig. 2, it can be noted that RG-DKF has the lowest convergence speed among these three different gossip-based DKFs. As GG-DKF picks up the optimal communication path for every local sensor node at each gossip iteration, it exhibits the fastest convergence rate at the expense of high communication burden. The proposed SGG-DKF only leverages a suboptimal communication path, i.e., performing greedy sensor selection within a set of randomly-chosen active sensor nodes. Therefore, the SGG-DKF provides tradeoff convergence performance between RG-DKF and GG-DKF. As the probability threshold in selecting the active node is $p = 0.5$, the proposed algorithm only requires half communication burden in the average sense at each iteration, compared to the GG-DKF. Interestingly, the performance of SGG-DKF is very comparable to that of the GG-DKF and its convergence rate is much faster than that of the RG-DKF for the random geometric sensor network topology even with $p = 0.5$.

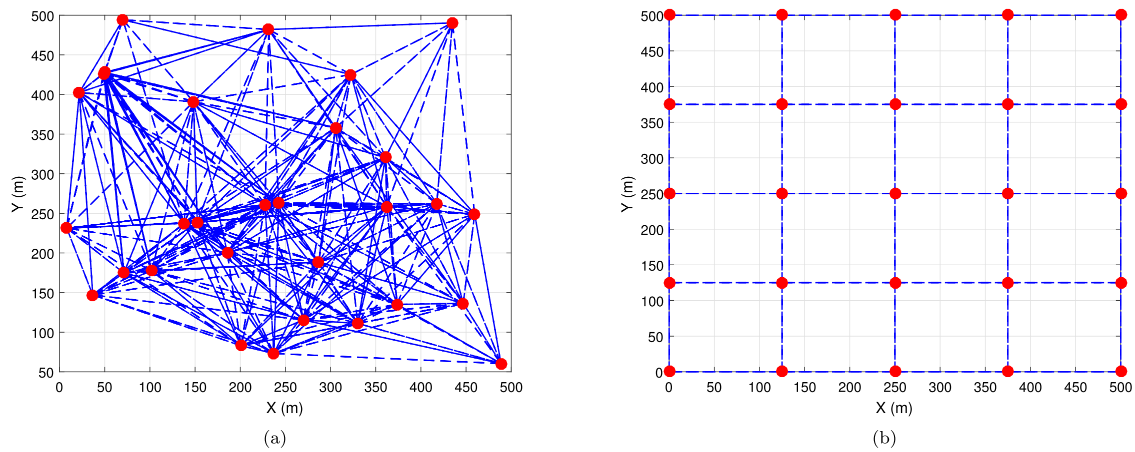

Fig. 1. Examples of two different network topologies. The red circles denote the sensor locations and the blue lines refer to the connections between sensor nodes. (a) Random geometric topology with each sensor being randomly placed inside the surveillance region and two sensors being connected if their relative distance is less than 300 m. (b) Deterministic grid topology with all sensors being placed as a grid shape inside the surveillance region.

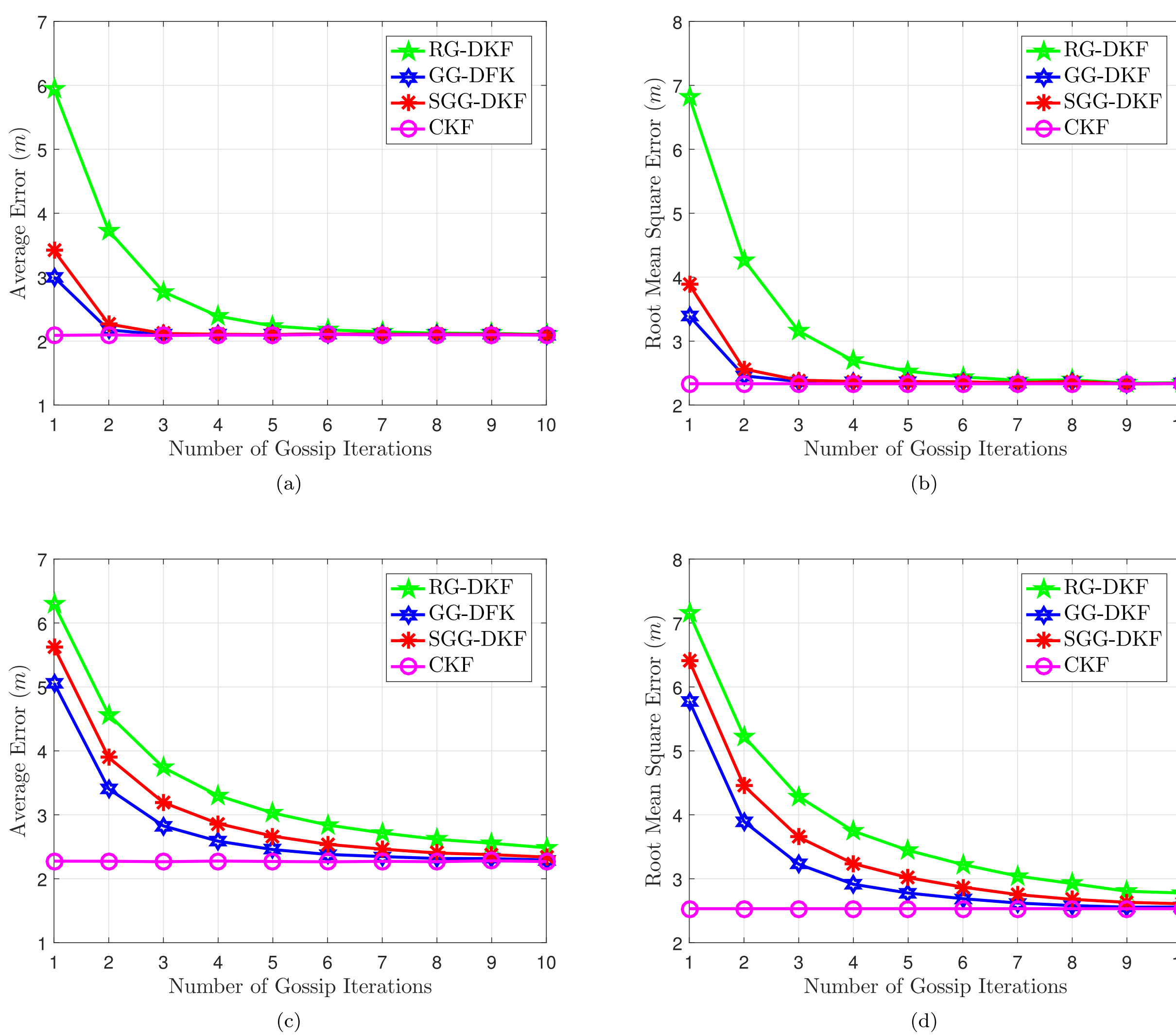

Fig. 2. Monte Carlo comparison results with respect to different number of gossip iterations. (a) ME comparison results for random geometric sensor network. (b) RMSE comparison results for random geometric sensor network. (c) ME comparison results for deterministic grid sensor network. (d) RMSE comparison results for deterministic grid sensor network.

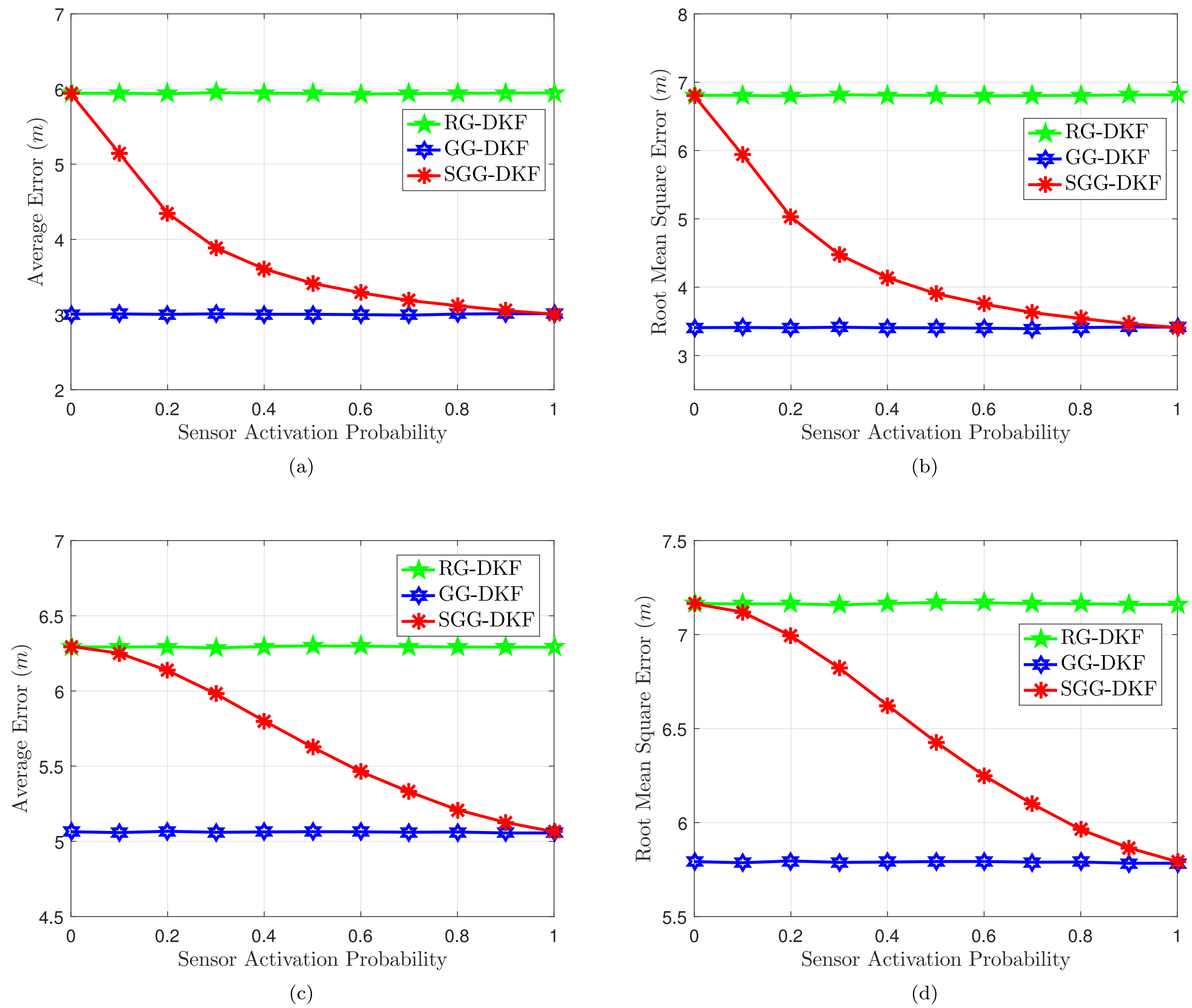

Fig. 3. Monte Carlo comparison results with respect to different sensor activation probabilities. (a) ME comparison results for random geometric sensor network. (b) RMSE comparison results for random geometric sensor network. (c) ME comparison results for deterministic grid sensor network. (d) RMSE comparison results for deterministic grid sensor network.

Now, let us investigate the effect of the sensor activation probability on the tracking performance. For this purpose, the number of gossip iterations in each Monte Carlo run is set as $L = 1$. Fig. 3 presents the comparison results of target position estimation ME and RMSE for different gossip-based DKFs with different sensor activation probabilities $p = 0, 0.1, \ldots, 1$ obtained from 500 Monte Carlo runs. From this figure, it can be observed that GG-DKF provides the best estimation performance among all the tested algorithms. This can be attributed to the fact that GG-DKF finds the optimal local sensor node for fusion. However, as stated before, this achievement requires each local sensor to communicate with all its connected neighbours at each iteration. As a comparison, the proposed SGG-DKF offers great flexibility and well balance between communication cost and convergence performance introduced by the stochastic sampling strategy. With the increasing of sensor activation probability, SGG-DKF provides improved estimation performance and converges to that of GG-DKF when $p = 1$. If the local sensor node cannot provide enough bandwidth for communication, a relatively small sensor activation probability can be selected to save the communication cost. When $p = 0$, the proposed algorithm becomes identical to RG-DKF. The results confirm that the proposed SGG algorithm is a generalised version of the randomised and greedy gossip algorithms.

5.4. Comparison with previous gossip-based distributed estimators

This subsection evaluates the advantage of the proposed SGG-DKF when the sensing ability is limited, which is the case in practice. For rigorous evaluation, we perform Monte Carlo comparisons with previous gossip-based DKFs, i.e., RG-MVF [30] and GG-MVF [31]. Each sensor node is assumed to be able to detect the target if the relative distance between the target and the sensor node is less than 100 m. In all simulations, the sensor activation probability for implementing SGG-DKF is set as $p = 0.5$.

The simulation results of target position estimation ME and RMSE obtained from 500 Monte Carlo runs are depicted in Fig. 4. It follows from Fig. 4 that the SGG-DKF still significantly outperforms both RG-MVF and GG-MVF, especially for the grid sensor network. This can be attributed to the fact that the proposed SGG-DKF utilises the information weighted fusion concept while RG-MVF and GG-MVF only leverage MVF in the fusion process. If one sensor cannot detect the target due to limited sensing range, the sensor node can only use target state prediction or the so-called prior estimation as the local state estimation, which generally has certain amount of estimation errors. Since RG-MVF and GG-MVF never utilise local prior knowledge in the fusion process, these two algorithms constrain the posterior estimates as the prior estimates if the sensor and its neighbours cannot detect the target

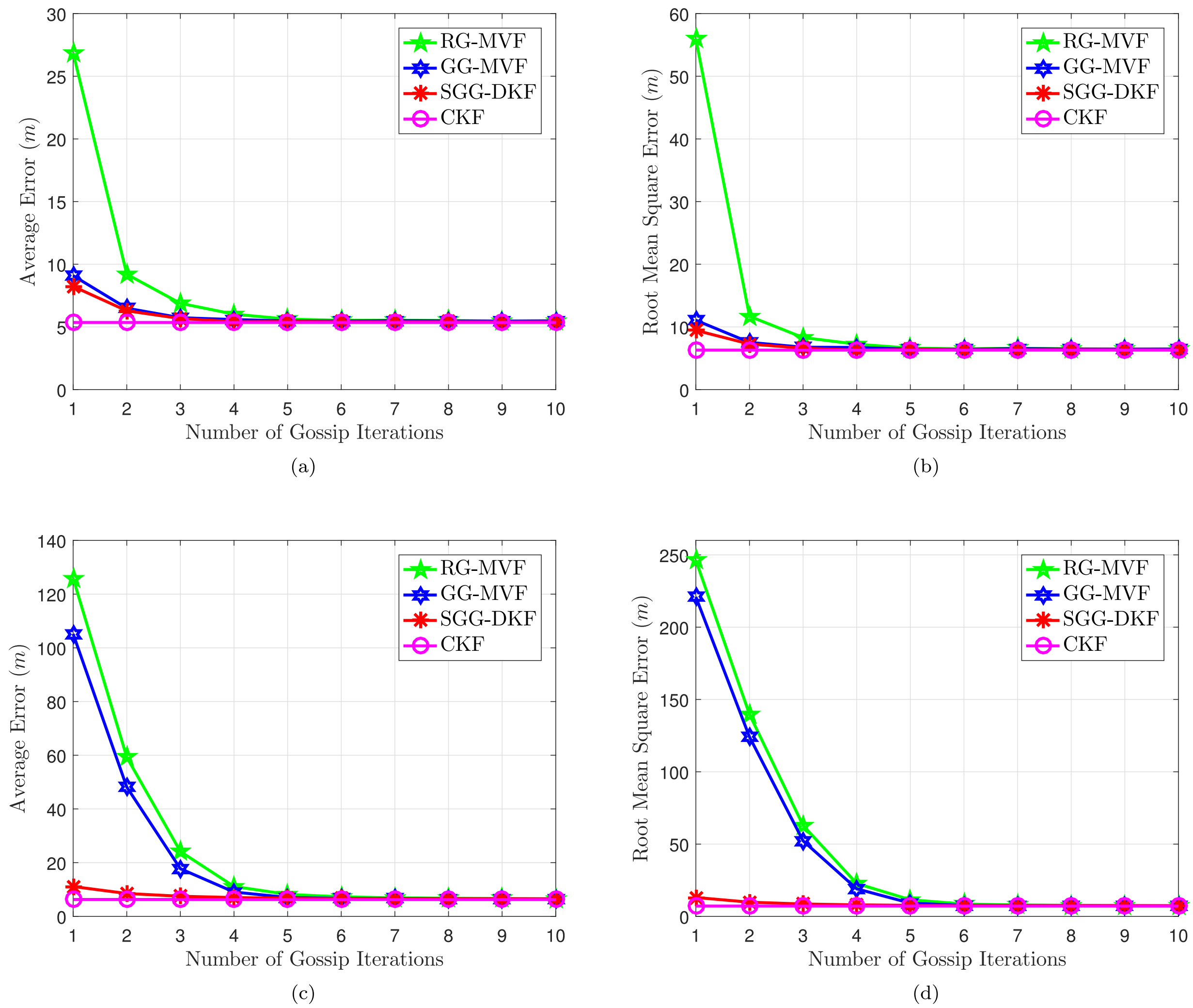

Fig. 4. Monte Carlo comparison results with respect to different number of gossip iterations. (a) ME comparison results for random geometric sensor network. (b) RMSE comparison results for random geometric sensor network. (c) ME comparison results for deterministic grid sensor network. (d) RMSE comparison results for deterministic grid sensor network.

due to limited gossip iterations. As a comparison, the prior estimation of each sensor node is weighted by the inverse of the corresponding error covariance in the proposed SGG-DKF during fusion. This handles the issue of naive sensors, i.e., target is outside of the sensor's field-of-view, by placing less weight when receiving the information from a naive neighbour sensor. Therefore, the proposed SGG-DKF is helpful in ensuring the consistency of local estimates and is demonstrated to generate better tracking performance when the number of gossip iterations is small.

5.5. Comparison with consensus-based distributed estimators

This subsection compares the performance of the proposed SGG-DKF algorithm with respect to consensus-based distributed estimators. As detailed in Section 1, the state-of-the-art IWCF algorithm enjoys the advantages of both consensus on information and consensus on measurement. Hence, the IWCF algorithm is performed in the simulations for the purpose of performance comparison. The sensor activation probability to implement the proposed SGG-DKF is set as $p = 0.5$. For simplicity, we assume that each sensor node has unlimited sensing range in this subsection.

The simulation results of target position estimation ME and RMSE obtained from 500 Monte Carlo runs are depicted in Fig. 5. From this figure, it can be noted that the proposed SGG-DKF and IWCF provide comparable convergence speed of the estimation error. However, the IWCF algorithm requires each local sensor node to communicate with all its connected neighbours. As a comparison, the proposed SGG-DKF algorithm can save half communication resource in the average sense and hence could be more suitable for practical applications.

6. Conclusions

This paper proposed a distributed sample greedy gossip distributed Kalman filter over a sensor network. The proposed algorithm utilises the concept of information weighted fusion in conjunction with the sample greedy gossip process. Rigorous asymptotic convergence and boundedness analysis of the proposed distributed estimation algorithm is carried out to support its applications. The empirical investigation demonstrates the validity of the theoretical analysis results. The prominent feature of the proposed algorithm lies in that it allows tradeoff between convergence rate and communication burden: our algorithm shows faster convergence speed, compared to the randomised gossip distributed Kalman filter, and requires less communication burden, compared to the greedy gossip distributed Kalman filter.

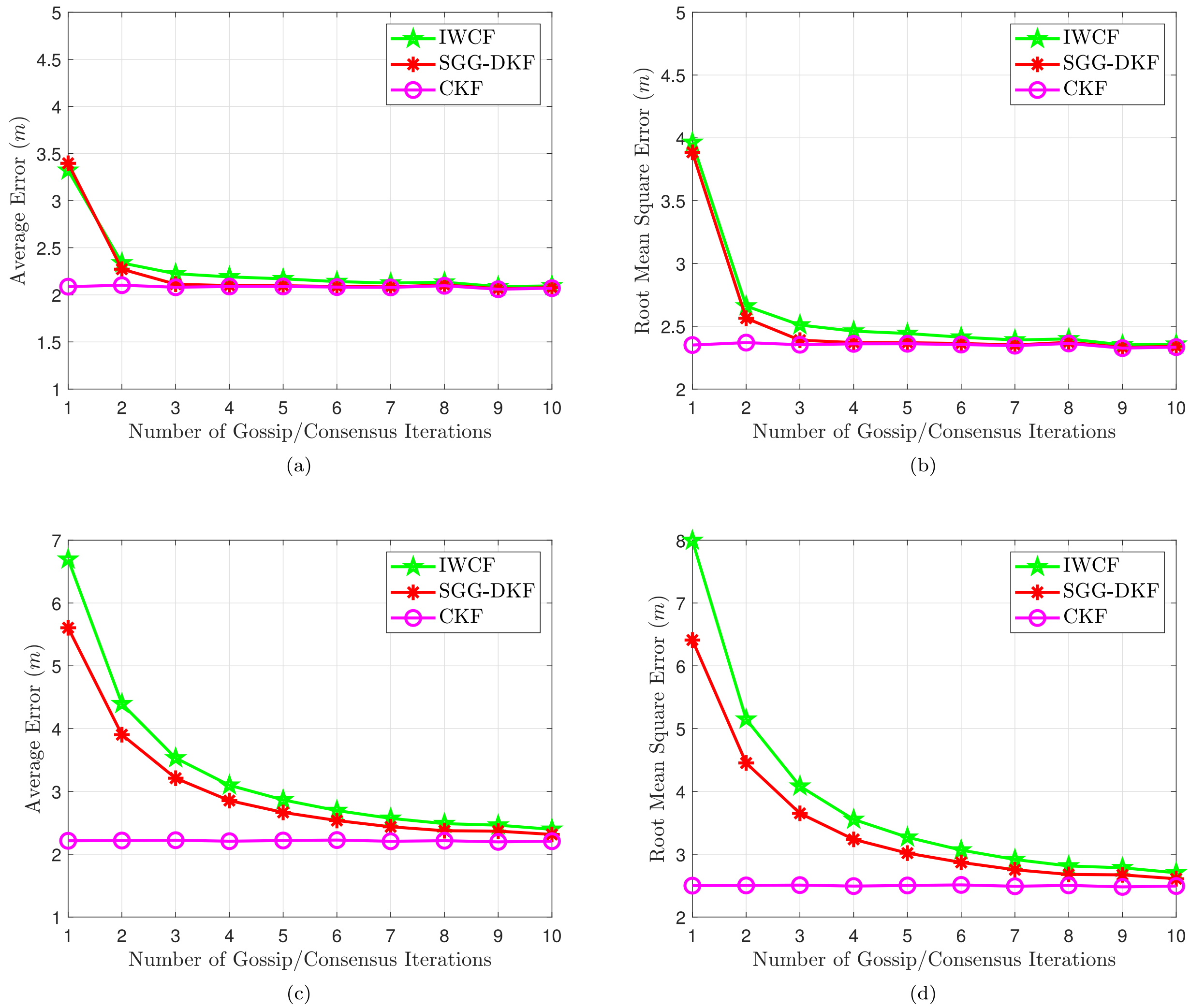

Fig. 5. Monte Carlo comparison results with respect to different number of gossip/consensus iterations. (a) ME comparison results for random geometric sensor network. (b) RMSE comparison results for random geometric sensor network. (c) ME comparison results for deterministic grid sensor network. (d) RMSE comparison results for deterministic grid sensor network.

CRediT authorship contribution statement

Hyo-Sang Shin: Conceptualization, Methodology, Software, Visualization, Investigation, Supervision, Validation, Writing - review & editing. **Shaoming He:** Methodology, Software, Investigation, Visualization, Validation, Writing - review & editing. **Antonios Tsourdos:** Validation.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Sample greedy gossip distributed Kalman filter

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